Development of a Novel Deep Learning Framework for the Automatic Rice Leaf Disease Detection and Classification

SHORT SYNOPSIS

Submitted in partial fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

by

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DECLARATION BY THE SCHOLAR

I hereby declare that the short synopsis entitled **Development of a Novel Deep Learning Framework for the Automatic Rice Leaf Disease Detection and Classification** being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in the Department of Computer Science & Technology under the School of Engineering of Manav Rachna University, Faridabad during the academic year 2025-26.

It is the work that is expected to be carried out under the supervision of Dr. Prinima Gupta, Professor, MRU and co-supervision of Dr. Mahboob Aalam, Associate Professor, MRIIRS.

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This is to certify that, the short synopsis entitled **Development of a Novel Deep Learning Framework for the Automatic Rice Leaf Disease Detection and Classification** is an original piece of work done by research scholar Anup Singh Kushwaha under the supervision of Dr. Prinima Gupta, Professor, MRU and co-supervision of Dr. Mahboob Aalam, Associate Professor, MRIIRS for the degree of Doctor of Philosophy in the Department of Computer Science & Technology under the School of Engineering of Manav Rachna University, Faridabad during the academic year 2025-26.

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ABSTRACT

Timely identification of leaf diseases in rice plants is essential for managing infection proliferation and improving food crop quality. Presently, numerous illnesses might diminish the output of rice harvests. The primary etiological agents of these illnesses in rice crops are bacteria, fungus, viruses, and specific detrimental insects. Diseases that influence the initial phases of rice production substantially affect the overall agricultural process. In the initial period, farmers conducted manual illness identification. It mostly encompasses the visual examination of crop diseases. This outdated method necessitates considerable time for disease classification, frequently leading to inaccuracies. Machine learning is an emerging technology for recognizing and classifying various diseases, effectively addressing the challenges associated with manual disease detection. Achieving the target necessitated an appropriate segmentation, feature extraction, and selection process. This study presents a modified faster regional convolutional neural network (MFRNet) utilizing deep learning for the automated detection and classification of rice leaf diseases within a cohesive framework. This study detects and categorizes four distinct types of rice leaf diseases: bacterial blight, sheath rot, brown spot, and blast. The proposed MFRNet enhances both the quality and quantity of rice yield by facilitating the recognition and discrimination of specific weeds, as well as the classification of rice leaf diseases.

Keywords: Rice Leaf, Machine Learning, Deep Learning, Faster Regional Convolutional Neural Network

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1. Introduction

1.1 Overview

The primary global need in agriculture is exceptional production; hence, many countries employ modern technologies to enhance the productivity of agricultural outputs. Advanced technology must guarantee a substantial rate of food production. Nonetheless, additional elements, including abiotic stressors (e.g., insects, diseases, drought stress, nutritional inadequacies, and weeds) and several pest categories, predominantly impact plants at any developmental stage **(Mahlein et al. 2012)**. These factors marginally influence the quality and quantity of agricultural goods. The identification of plant diseases is essential yet challenging. This requires vigilant observation of the paddy leaf to assess its status for disease infestation. Diseases predominantly impact both post-harvest productivity and production. Previously, the severity of illness in plants could only be assessed using visual inspection procedures. The precision of this study primarily relies on the expertise and understanding of the analyst. The extensive cultivation area necessitates considerable time for visual examination and demands continuous human monitoring. Consequently, a mechanism is required to supplant the manual analytical procedure.

1.2 Plant Diseases

The plant infection impairs **(Patil and Kumar 2017)** the physiological functions of the plant and inflicts considerable harm to the field. Moreover, plant diseases can disseminate to other plants through multiple avenues. Every plant disease exhibits signs in different areas of the crop, such as roots, fruits, leaves, flowers, and stems. Plant diseases can induce unwarranted alterations in the morphology and dimensions of fruits, leaves, flowers, and stems. Figure 1 illustrates the various categories of plant diseases.

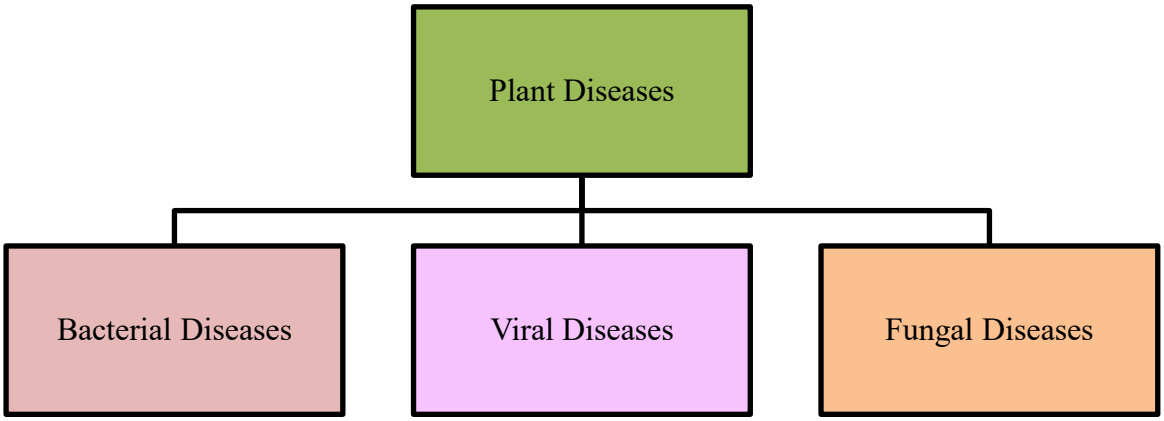


Figure 1: Different types of plant disease

Plant diseases diminish agricultural output by impacting both the amount and quality of the produce. Rice is the primary food crop in Asian nations. To satisfy the substantial demand for rice, researchers have devised many methods to enhance crop production. This cereal is cultivated in extensive paddy fields; hence the proliferation of any disease would significantly impact productivity. Numerous biological variables, outlined in Table 1, induce the plant to develop these detrimental illnesses.

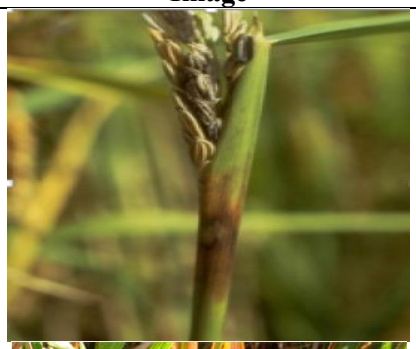
Table 1: Description of Various Diseases in Rice Plant

Type of Disease	Description
Bacterial Diseases	Bacterial diseases relate to plant illnesses caused by bacteria. Bacterial leaf spot is a plant disease that typically arises from bacterial infection. It predominantly impacts young leaves, manifesting as black, oily, contorted, water-saturated lesions.
Viral Diseases	Viral infections impact both plant vitality and agricultural yield. In viral infections, symptoms primarily manifest on the plant leaves; however, certain viruses may also impact other plant parts, including roots, stems, and fruits. Recognizing the signs of viral infections is more difficult than recognizing those of bacterial diseases.
Fungal Diseases	Fungal infections can disseminate across plants by agents such as water and wind. It impacts the seed, yield, and soil quality. The plant infected by the fungal disease has water-soaked, grey-green lesions. It disseminates across the leaf surface, resulting in a yellow discoloration.

1.3 Rice Leaf Diseases

Diseases, pathogen incursion, and climate factors substantially influence agricultural yield annually. Weather conditions must be considered, whereas the spread of diseases and infections may be managed. Table 2 **(Majumdar et al. 2014**) presents several diseases that typically affect rice leaves.

Table 2: Description of Rice Leaf Disease

Disease	Cause	Symptoms	Image
Sheath rot	Fungal	• Rotting of leaf sheath • Grayish-brown lesions with irregular margins • White fungal growth	
Leaf blast	Fungal	• Diamond-shaped gray lesions with brown borders • Lesions enlarge, causing leaf curling and drying	
Leaf smut	Fungal	• Black, slightly raised spots on leaf surface • Spots can coalesce, leading to leaf discoloration and drying	
Brown Spot	Fungal	• Circular to oval brown spots with a gray center • Severely affected leaves turn yellow and dry	

Bacterial blight	Bacterial	• Yellowish water-soaked lesions on leaves • Lesions enlarge, becoming brown and drying • Wilting of young plants	

1.4 **Deep Learning Implementation**

Fig 2 shows the genitalized steps involved in the development a deep leaning based classification model. The steps are discussed below:

- **Input Image:** This is the starting point where raw images of rice leaves are collected. These images capture various leaf conditions, including healthy leaves and those affected by different diseases.
- **Data Pre-processing:** Pre-processing involves cleaning and preparing the input images for analysis. It includes Resizing images to a fixed dimension for uniformity. Converting images to grayscale or maintaining RGB format based on model requirements. Normalizing pixel values to scale data between 0 and 1. Removing noise or irrelevant parts of the image.
- **Data Augmentation:** Augmentation artificially increases the size and diversity of the dataset by creating modified versions of the input images. The major operation involved are Rotation, flipping, cropping, zooming, adjusting brightness, contrast, saturation, and adding random noise or applying filters.
- **Data Splitting:** The dataset is divided into training, validation, and testing subsets. The common proportion are 70-80% for training, 10-15% for validation, and 10-20% for testing.
- **Deep Model Training:** This step involves using deep learning algorithms, such as CNNs or object detection frameworks like YOLO or Faster R-CNN, to train the model on the processed data.
- **Performance Evaluation:** The trained model is tested and evaluated to measure its effectiveness in detecting and classifying diseases. The major metrics are Accuracy, Precision, Recall, and F1-Score for classification. Mean Average Precision (mAP) for object detection.

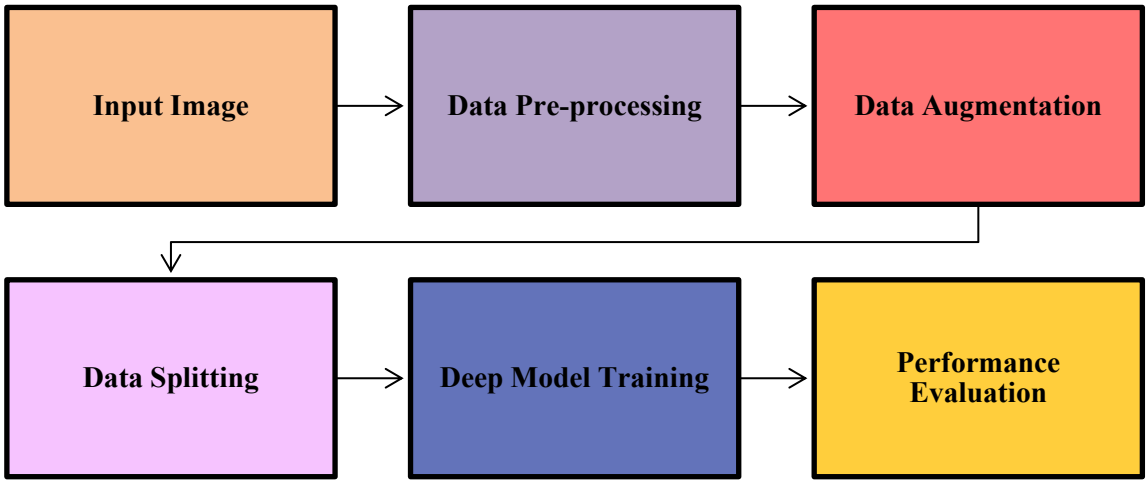


Fig 2: General steps involved in the design and development of a deep learning-based classification and detection model

2. Literature Reviews

In literature, various methods had been developed to classify and detect the rice leaf disease. The DL-based object detection methods are an emerging trend that provides the detection of abnormal instances and categorization of diseases. Some of the existing states of the arts are summarized as follows.

Trinh et al. [7] presented a variant of the you only look once (Yolo) model for the detection and classification of RB, BS, and leaf folder RLD. The base model employs Yolov8, which was modified in terms of the loss function for bounding boxes by an efficient and alpha intersection over union loss (IoU) function. The performance was evaluated on self-acquired RLD images. The achieved accuracy was 89.9%. However, there was no image enhancement to improve the quality of rice leaf images. Furthermore, no comparative qualitative assessment was conducted to validate the work.

Cao et al. [8] employed Yolov8 for rice leaf disease detection, and classification (RLDDC). The backbone module includes coordinates for the feature layer, which was modified by incorporating a convolutional block attention module (CBAM). The evaluation was conducted using self-captured images of rice leaf diseases image dataset (RLDID). The obtained mean average precision was 84.3%. However, it was not specified which type of RLD was either categorized or detected.

Pan et al. [9] exhibited a two-step framework for the detection of RB and its variant. The first step included a Yolo-X to identify the abnormal region of interest (RoI). Furthermore, the detected RoIs were classified by the Siamese network. The performance was measured on self-acquired RLD images. The overall accuracy was 98.31%. However, the method concentrated on classifying and detecting different types of rice blasts. Moreover, no comparative qualitative assessment was provided to judge the effectiveness of the method.

Rajpoot et al. [10] used a faster regional convolutional neural network (FRCNN) with VGG16 to extract the features from rice images. Furthermore, a random forest was applied to the feature maps for

classification of RLD as BS, BB, and leaf smut. The methodology was devised for the rice leaf image dataset obtained from the UCI ML repository. The attained accuracy was 97.3%. However, there was no visual assessment to evaluate the efficacy of the method. Additionally, it was also unclear which data enhancement method was applied to improve the quality of data.

Aziz et al. [11] used Yolov5, which was developed based on the principle of transfer learning, for the detection of RLD. It was developed for RB, BB, BS, and Hispa identification. The method was designed for a freely available rice leaf image dataset. The achieved accuracy was 94%. However, there was no modification in the base model. Moreover, no comparative qualitative evaluation had been done to measure the effectiveness of the method. Apart from this, training the model on a smaller dataset resulted in overfitting.

Shaikh et al. [12] employed FRCNN for RLDDC in terms of RB, BS, and Hispa, respectively. The method was cast to open accessible datasets. The overall accuracy was 84.56%, indicating limited performance. However, the base model was remained unmodified. Furthermore, only the detection outcome of BB was presented. Besides this, there was no comparative qualitative and quantitative evaluation for judging the method's efficacy.

Wang et al. [13] adapted Yolov8, where the backbone network was altered with MobileNetv4 and the focal attention module (FCM) for the RLDDC. It was developed for the self-acquired image datasets to identify the rice disease primarily RB, BB, and BS. However, the confidence score of classification and detection outcome was limited. Furthermore, the work lacked a comparative visual assessment to validate it.

Trinh et al. [14] employed Yolov8 with a wise loss function for IoU bounding boxes for RLDDC. The performance was evaluated on self-acquired RLD images. The achieved accuracy was 89.2%. However, no data refinement took place. The result detection and class score were also moderate. Furthermore, the work did not undergo a comparative qualitative and quantitative assessment for validation.

Wang et al. [15] presented a Yolov8-based model of RLDDC. The backbone module clubs a modified CBAM for feature extraction. Moreover, a structural reparameterization module was also introduced for feature mapping. The method was developed for an openly accessible RLD dataset on Kaggle for RB, BB, BS, and planthopper correspondingly. The obtained precision was 86.2%. However, the method's efficacy did not receive a comparative visual evaluation.

Fu et al. [16] and **Kiratiratanapruk et al.** [17] employed a variant of Yolov8 for RLDDC. The backbone module of both these methods was modified with the aid of an attention mechanism and image tiling, respectively. These methods were primarily developed for RB, BB, and BS, respectively. Both methods were cast on a publicly assessable dataset. The obtained mean average precision by these methods was 88.8% and 91.70%, respectively. However, no image enhancement or comparative qualitative assessment was performed to measure the wellness of the method.

Bari et al. [18] adopted FRCNN for RLDDC. The method was formed for a publicly available and self-captured rice leaf image dataset. The RLD categorization was achieved for BB, RB, and Hispa, respectively. The obtained average accuracy was 98.70%. However, there was no modification in the base model. Moreover, no comparative qualitative evaluation had been done to measure the effectiveness of the method. Despite this, there was no data refinement to improve the image quality.

Haque et al. [19] employed Yolov5 for the RLD categorization and detection. The method was developed for self-captured RLDID. The method was primarily established for BB, RC, and BS. The obtained mean average precision was 90%. However, the primary model remained unmodified. Furthermore, no

comparative qualitative and quantitative assessment had been conducted amid the existing object detection methods to evaluate the efficacy of the method.

Yang et al. [20] used a detection transformer (Detr) for the RLDDC. In this method, Res2Net was employed as a backbone module. Furthermore, dense higher-level composition (DHLC) was also added in the feature pyramid network. The method was designed for a freely available dataset of rice leaf images, which was acquired from the image database for agricultural diseases and pests research (IDADP). It primarily classifies and detects RB, BS, and sheath blight. The obtained average accuracy was 97.44%. However, the work lacked a comparative visual assessment to validate it.

Haruna et al. [21] adapted Yolov7 by including a modified the feature pyramid network. It introduces a self-attention with register-based pyramid feature fusion (SaRPFF). It was a combination of multi-head self-attention with register tokens. The method was applied on an openly accessible RLDID. It was used to detect and classify RB and BS. The obtained mAP is equal to 69.66%. Moreover, no comparative qualitative analysis has been performed among the current object detecting technologies to assess the effectiveness of the technique.

Sankareshwaran et al. [22] employed a RetinaNet-based method for RLDDC. The method includes a channel attention module with ResNet50 as a backbone module for feature extraction. Moreover, they had applied a crossover boosted artificial hummingbird algorithm (CBAHA) for hyperparameter tuning. The method was developed for self-collected and publicly available rice leaf disease datasets in terms of healthy and unhealthy rice leaves. The achieved accuracy as 98.1%. However, neither the developed method nor a comparative study included a qualitative evaluation.

Literature shows that the existing state of the arts of RLDDC has primarily focused on FRCNN, Detr, RetinaNet, Yolo, and its different variants. These are popular object detection methods. These methods have been developed for self-acquired as well as publicly available RLDD. The majority of existing methodologies cater to RB, BB, and BS RLD. However, the existing methodologies have limited performance in terms of data refinement, visual, and statistical assessments. Furthermore, the majority of existing methodologies have employed imbalanced RLDID, which is another major issue and leads to the overfitting of the models. The existing state of the arts of RLDDC has low efficacy in terms of precise ROI detection of abnormalities in rice leaves. This issue arises due to the overlapping of bounding boxes and low visibility of RoIs. The backbone module of existing methodologies performs inadequate feature extraction on input images. It affects the mapping of fine details of rice leaf disease. Therefore, to overcome these issues, there is an automated deep framework that provides the precise detection and multi-label classification of rice leaf disease in a unified frame. Table 2 highlights the key and significant contribution of the existing RLDDC methods.

2.1 Existing Methodologies for Rice Leaf Disease Detection and Classification

Ref.	Disease Class	Model	Dataset	Metrics	Result	Remark
(Sun et al. 2024)	Rice panicle	Yolov2 and Efficienetv2	Self-generated dataset	Accuracy	92.60%	Performance is limited as low accuracy.
(Cao et al. 2024)	Rice leaf blast	Yolov8	Self-acquired dataset	Average Precision	84.3%	Only single class of rice leaf disease is detected and classified.

(Ritharson et al. 2024)	Rice blast, Bacterial leaf blight	VGG16, Xception, ResNet50, DenseNet121, Inception ResnetV2, and Inception V3	RDID	Accuracy	99.94%	Performs only classification.
(Mehzabeen and Gayathri 2025)	Bacterial leaf blight, bacterial leaf streak, bacterial panicle blight, blast, brown spot, dead heart	LSTM with attention module	RDID	Accuracy	96%	Performance is limited.
(Rajpoot et al. 2023)	Rice blast, Bacterial leaf blight, Sheath Blight, Leaf smut, Sheath Rot, Brown Spot	Faster RCNN	UCI Machine Learning Repository	Accuracy	97.3%	No modification in the base model.
(Karantoumanis et al. 2024)	Bean Leaf	Yolov5	PlantDoc	Accuracy	82.%	Low performance.
(Pan et al. 2023)	Rice panicle neck blast, rice false smut, rice leaf blast	Yolox	Self-acquired rice leaf dataset	Accuracy	95.58%	Performance is limited
(Rawat et al. 2023)	Bacterial Leaf Blight, Brown spot, Leaf smut	ResNet 50 with added Neural Network	Self-generated rice leaf database	Precision, Recall, F1 score, Accuracy,	ACC-99.2%	Performed only classification.
(Haridasan et al. 2023)	Leaf blast, Sheath rot, false smut, bacterial leaf blight	CNN	Self-generated database	Precision, Recall, F1-score	88.93%	Performance is limited and worked only for classification.
(Stephen et al. 2023)	Brown Spot, Hispa, Leaf Blast	ResNet34, ResNet 50, ResNet 18	Rice leaf disease from Kaggle	Accuracy, specificity, F1 score,	98.54%	Model was trained on small dataset.
(Win Lwin and Htwe 2023)	Healthy Rice Leaf, rice Leaf Blight	AlexNet, VGG16, CNN	Rice leaf disease from Kaggle	Accuracy	98.05%	No detection of affected region.
(Gopi and Kishan Kondaveeti 2023)	Bacterial Blight, Brown Spot, Leaf smut, Tungro	DenseNet 169, Xception	Mendeley data and Kaggle repository	Accuracy	99.66%	No detection mechanism.
Zhou et al., 2020	Bacterial Leaf Blight, Blast, Brown Spot	CNN (ResNet50)	Custom dataset (10,000+ images)	Accuracy, Precision, Recall	97.3%	High performance on high-quality

						images
Patil & Bodhe, 2011	Blast, Brown Spot	SVM + Image Processing	Field images from Maharashtra, India	Accuracy	86.5%	Classical method; less effective for large datasets
Too et al., 2019	Blast, Brown Spot, Tungro	CNN (MobileNet, DenseNet)	PlantVillage + augmented images	Accuracy, F1-Score	Up to 98.2%	Efficient on mobile platforms
Lu et al., 2017	Leaf Blast	Deep CNN	Custom dataset (public + field data)	Accuracy	95.1%	Handles noisy backgrounds
Sladojevic et al., 2016	Multiple crops incl. rice	CNN	PlantVillage	Accuracy	~96% for rice	Limited to lab conditions
Mohanty et al., 2016	Rice Leaf Spot	Deep Learning (AlexNet, GoogLeNet)	PlantVillage	Accuracy	99.35%	Best under controlled lighting
Amara et al., 2017	Rice Leaf Disease	CNN	Leaf images from Tunisian Institute	Accuracy	93%	Small-scale dataset
Rodrigo et al., 2024	Multiple rice leaf diseases	MobileViTV2_050 (CNN + ViT)	Custom rice leaf dataset	Accuracy, F1-Score, ROC	99.6% accuracy, 93% F1-score	Lightweight model, suitable for mobile apps
Gnanavel & Periyathambi, 2025	Rice leaf diseases	Faster Hierarchical ViT (FHViT)	Ade F. Rice Leaf Diseases (AFRLD)	Accuracy, Precision, Sensitivity, Specificity, Recall, F1-score	99.2% accuracy, 99.0% F1-score	Efficient with reduced computational load
Sudhesh et al., 2025	Rice leaf diseases with severity estimation	Vision Transformer (ViT)	Custom dataset (3,345 images)	Accuracy	77.94% weighted avg. accuracy	Dual-task model for type and severity
Yang et al., 2023	Sheath blight, rice blast, flax spot	DHLC-DETR	IDADP rice disease dataset	Mean Average Precision (mAP)	97.44% mAP	Enhanced small object detection
Sobuj et al., 2024	Rice leaf diseases	EfficientNet-B7 + HOG + Grad-CAM	Custom dataset	Accuracy	97% accuracy	Improved feature extraction
Mehnaz & Islam, 2025	Bangladeshi rice leaf diseases	ResNet50, ViT, SVM	Dhan-Shomadhan	Accuracy	ResNet50 outperformed others	CNNs outperformed ViT and SVM

Pandiyaraju et al., 2024	Paddy leaf diseases	Hybrid CNN with Channel Attention and Swish ReLU	Custom dataset	Accuracy, F1-score	99.74% accuracy, 99.76% F1-score	High classification performance
DeepRice, 2023	Nine rice leaf disease classes	Custom VGG16 model	Self-generated (5,932 images)	Accuracy	99.94% accuracy	High generalization and interpretability

2.2 Challenges and Issues

The following challenges and issues are outlined from the literature:

- The existing detection, and classification of rice leaf diseases using deep learning has limited performance and efficacy.
- The exiting works doesn't offer the multi-instance rice leaf disease detection, and classification.
- The existing work failed to offer a real time rice leaf diseases monitoring system for the farmer.
- The existing methods employs small and imbalanced datasets for the development of the method.
- The DL-based methods have an issue with overfitting and dropout.
- The exiting methods has low accuracy, precision, sensitivity, and specificity.

2.3 Dataset Description

The following are some common image datasets of rice leaves used in research projects:

(1) Rice Disease Image Dataset (RDID): This dataset includes images of rice leaves affected by bacterial leaf blight, brown spot, blast, and other diseases. It has a rich collection of 5932 images. This dataset presents a comprehensive array of visuals, encompassing four distinct types of rice leaf diseases: bacterial blight, blast, brown spot, and Tungro.

(2) Rice Leaf Diseases Dataset (RLDD): The Rice Life Disease Dataset is an extensive collection of data focused on three major diseases that affect rice plants: Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS). The dataset has been curated to assist researchers, agronomists, and machine learning practitioners in understanding, diagnosing, and potentially predicting the occurrence of these diseases, based on various attributes and parameters.

(3) Rice Leaf Diseases (RLD): There are three classes/diseases: Bacterial leaf blight, Brown spot, and Leaf smut, each having 40 images. The format of all images is jpg.

The overall summary of the public dataset is shown in Table 2.

Dataset Name	Number of images	Total Classes	url
RDID	5932	4	https://data.mendeley.com/datasets/fwcj7stb8r/2
RLDD	4684	3	https://data.mendeley.com/datasets/dwtn3c6w6p/1

RLD	120	3	https://archive.ics.uci.edu/dataset/486/rice+leaf+diseases

3. Research Problem and Objectives

The production of rice is essential for the supply of food, as it is consumed by millions globally. Rice crops are vulnerable to numerous diseases that can markedly diminish output and quality. Prompt and precise identification of these diseases is essential for timely intervention and efficient crop management. Conventional disease detection methods, dependent on human skill, are laborious, subjective, and inefficient, especially in extensive agricultural environments.

Recent breakthroughs in deep learning have facilitated automated, precise, and scalable systems for disease identification. Utilizing object detection methodologies, the proposed work may create systems that recognize and classify various rice leaf diseases from images.

3.1 Problem Statement

"To develop a framework for the detection and classification of rice leaf diseases using low computational resources leading to an increase in crop production."

The study seeks to bridge the gap by examining and contrasting current deep learning models for the detection and classification of rice leaf diseases within a unified framework. Additionally, it seeks to identify bacterial blight, leaf blast, brown spot, sheath blight, and tungro disease, among others. Additionally, it seeks to tackle issues such as acquiring extensive, high-quality datasets, regulating fluctuations in illumination and ambient conditions, and assuring resilience among various rice cultivars.

Moreover, creating models that necessitate reduced computational resources can render these solutions attainable for small-scale farmers.

3.2 Objectives

The research will adhere to the following objectives:

1. To conduct a pilot literature survey to identify rice leaf disease detection, and classification using deep learning.
2. To analyse and pre-process the available dataset in order to overcome the issues such as imbalanced dataset, and overfitting.
3. To develop a deep model for rice leaf disease detection, localization, and classification and assess its efficacy.
4. To investigate the performance analysis among the existing deep learning models and the proposed method for rice leaf disease.

4. Methodology

This section outlines and explains the proposed methodology, as shown in Fig. 3.

A. Dataset Collection: Data collection on rice image leaf covering various diseases under diverse environmental conditions.

B. Data Preparation: It includes data preprocessing, augmentation, dataset splitting and annotation of the data. Data annotation highlights the diseased regions and their corresponding disease categories for training and evaluation.

C. Model Design and Implementation: The primary objective of this project is to create and assess a reliable system for the identification and classification of rice leaf diseases utilizing advanced deep learning object detection methods. It includes the design and development a modified faster regional convolutional neural network (MFRNet) utilizing deep learning for the automatic detection, and classification of rice leaf diseases within a cohesive framework.

D. Optimization and Performance: This step emphasizes the optimization of model architectures to achieve high accuracy, low latency, and real-time performance in the identification and classification of rice leaf diseases. The suggested models would utilize rice leaf image data for training, employing approaches such as mini-batch training and gradient descent optimization.

F. Comparison and Analysis: This study seeks to evaluate the performance of the models utilizing criteria such as precision, recall, F1-score, mean average precision (mAP), and inference time. To

ascertain whether each method is superior or inferior to another regarding the accuracy of its detection and categorization. Evaluate and assess the proposed methodology in relation to conventional approaches and leading-edge deep learning techniques.

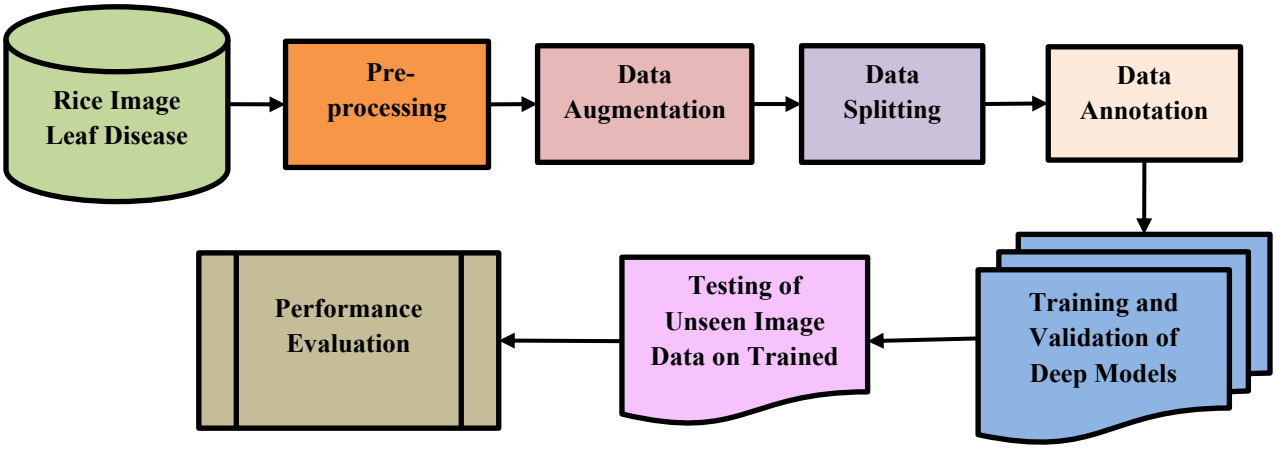


Fig. 3: Outline for the research objective

5. Expected Outcomes

The expected outcomes of this research are as follows:

1. **Disease Localization and Classification:** The developed deep learning-based model for rice leaf disease detection and classification is anticipated to surpass conventional methods in accuracy. It provides precise localization of diseased regions on rice leaves. Accurately classify diseases into predefined categories, such as bacterial blight, leaf blast, sheath blight, and others.
2. **Contribution to Sustainable Agriculture:** Exhibit how the proposed method facilitates early disease identification, mitigates pesticide overuse, decreases crop losses, and fosters sustainable agricultural methodologies. Test the model's robustness across varying conditions, including lighting, resolution, and different rice varieties.
3. **Scalability and Adaptability:** The proposed method should be scalable so as to handle other plant disease datasets while also being adaptable to changing environmental variables over time.
4. **Farmer-friendly Application Development:** Research futures aim to develop a user-friendly interface, such as a smartphone or online application, enabling farmers to input photographs and obtain real-time disease diagnoses and management advice. Investigate hardware compatibility for system deployment on drones or mobile devices for real-time field applications.

Further, this research is also focusses on the following publication specific outcomes:

1. Publication of two conference papers presenting novel findings and methodologies related to the development and evaluation of the deep learning-based rice leaf disease detection, and classification.
2. Publication of two peer journal articles detailing comprehensive analyses, comparisons of existing deep learning techniques, and the performance evaluation of the proposed method, as well as future research directions in this rapidly evolving field.

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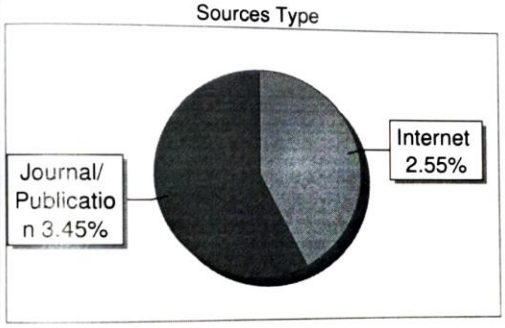

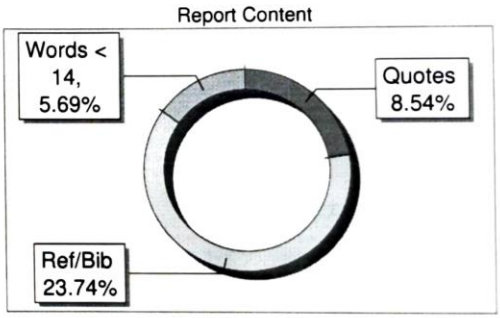

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SHORT SYNOPSIS

by

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Year 2025

ABSTRACT

Timely identification of leaf diseases in rice plants is essential for managing infection proliferation and improving food crop quality. Presently, numerous illnesses might diminish the output of rice harvests. The primary etiological agents of these illnesses in rice crops are bacteria, fungus, viruses, and specific detrimental insects. Diseases that influence the initial phases of rice production substantially affect the overall agricultural process. In the initial period, farmers conducted manual illness identification. It mostly encompasses the visual examination of crop diseases. This outdated method necessitates considerable time for disease classification, frequently leading to inaccuracies. Machine learning is an

emerging technology for recognizing and classifying various diseases, effectively addressing the challenges associated with manual disease detection. Achieving the target necessitated an appropriate segmentation, feature extraction, and selection process. This study presents a modified faster regional convolutional neural network (MFRNet) utilizing deep learning for the automated detection and classification of rice leaf diseases within a cohesive framework. This study detects and categorizes four distinct types of rice leaf diseases: bacterial blight, sheath rot, brown spot, and blast. The proposed MFRNet enhances both the quality and quantity of rice yield by facilitating the recognition and discrimination of specific weeds, as well as the classification of rice leaf diseases.
Keywords: Rice Leaf, Machine Learning, Deep Learning, Faster Regional Convolutional Neural Network

1. Introduction

1.1 Overview

The primary global need in agriculture is exceptional production; hence, many countries employ modern technologies to enhance the productivity of agricultural outputs. Advanced technology must guarantee a substantial rate of food production. Nonetheless, additional elements, including abiotic stressors (e.g., insects, diseases, drought stress, nutritional inadequacies, and weeds) and several pest categories, predominantly impact plants at any developmental stage **(Mahlein et al. 2012)**. These factors marginally influence the quality and quantity of agricultural goods. The identification of plant diseases is essential yet challenging. This requires vigilant observation of the paddy leaf to assess its status for disease infestation. Diseases predominantly impact both post-harvest productivity and production. Previously, the severity of illness in plants could only be assessed using visual inspection procedures. The precision of this study primarily relies on the expertise and understanding of the analyst. The extensive cultivation area necessitates considerable time for visual examination and demands continuous human monitoring. Consequently, a mechanism is required to supplant the manual analytical procedure.

1.2 Plant Diseases

The plant infection impairs **(Patil and Kumar 2017)** the physiological functions of the plant and inflicts considerable harm to the field. Moreover, plant diseases can disseminate to other plants through multiple avenues. Every plant disease exhibits signs in different areas of the crop, such as roots, fruits, leaves,

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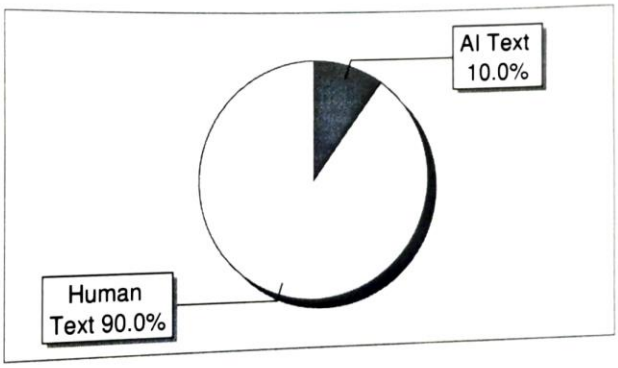

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